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Finite Element Learning Modules as Active Learning Tools

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ABSTRACT

The purpose of active learning is to solicit participation by students beyond the passive mode of traditional classroom lectures. Reading, writing, participating in discussions, hands-on activities, engaging in active problem solving, and collaborative learning can all be involved. The skills acquired during active learning tend to go above and beyond basic comprehension of information covered during a lecture. In fact, the goal of active learning is to not only enable student comprehension, but also to assist the student in cultivating valuable aptitudes for synthesizing, analyzing,



and evaluating ideas and their learning potential. This captures a significantly larger portion of the Bloom's Taxonomy than would be available in a lecture-only situation.

One model for active learning takes the form of tutorials, or more accurately described as active learning modules (ALMs), aimed at improving student learning in historically difficult subject areas in engineering through the application of finite element analysis. The tutorial set developed here includes learning modules for various subject areas in Mechanical, Electrical, and Biomedical Engineering courses.

The aim of this study is to determine if ALMs of this type are, in fact, effective active learning tools. In each participating course, after the student completes their traditional lecture series, they are introduced to a computer-based ALM. In order to perform a baseline study, students are administered content quizzes before and after the completion of the module. These quiz results are statistically analyzed to determine if subject aptitude, including comprehension, is improved. The incorporation of a novel assessment methodology reinforces the project goals as we are able to judge if these modules afford all students with an equal active learning process experience. The ALMs are shown to be a successful step towards improving aptitude and comprehension of challenging engineering content in an active learning environment.

INTRODUCTION

In the quest to improve engineering education, the active learning methods must be designed, assessed, and implemented properly. These pedagogical techniques have not yet been fully developed in engineering curriculum, especially within core courses (Wankat and Oreovicz 1993; Wood, Jensen et al. 2001; Jensen, Rhymer et al. 2002). For this current work, we consider active learning to be anything that goes beyond the traditional model of students passively listening to a lecture. Hands-on activities, problem based learning, interactive software and collaborative learning are all specific pedagogical techniques that are integrated into our learning module-based active learning repertoire in order to enhance students' experiences in the engineering classroom. Such active learning approaches have the potential to improve student comprehension and knowledge retention and also to increase students' interest in the material (Linsey, Talley et al. 2007). The main goal in this current work is to present the design, development, and assessment of one type of active learning tool, i.e. finite element (FE) learning modules. Effectiveness of these active learning modules (ALMs) is assessed based on improvement in student performance in general coupled with equitability of learning enhancement across a variety of student demographic groups.

Twelve ALMs were designed based on active learning pedagogical research. They were then evaluated in various classroom settings. Traditional lectures in selected engineering courses in the



Mechanical, Electrical and Biomedical Engineering fields of study were supplemented with these ALMs. Two overall project goals drive the details of the design, implementation and assessment of the ALMs. These overall project goals are:

1. Use the ALMs to provide a method to enhance students' understanding of conceptually difficult engineering concepts,
2. Use the ALMs to provide a baseline exposure to the FE method of engineering analysis.

A methodical process is used to implement and assess the ALMs. Participating students are given a quiz to evaluate their baseline understanding of historically difficult engineering topics. This is labeled the "pre-quiz". Then the FE-based ALMs are administered and the same quiz is retaken. This is called the post-quiz. This procedure is used, from a holistic viewpoint, to assess if these ALMs are accomplishing the goal of improving student learning.

Noting that the quizzes are designed to evaluate students' ability to accomplish specific learning objectives, the effectiveness of the ALMs is measured by the increase in post-quiz (taken after the ALM) scores over pre-quiz (taken before the ALM) scores. Additionally, improvements in quiz scores are correlated to learning styles, personality types and other demographic variables, followed by the application of basic statistical analysis. The end goal is to assess the effectiveness of the ALMs in two specific manners. First, the general effectiveness of the ALMs is measured by considering the overall improvement of the students' post-quiz scores over their pre-quiz scores. Second, quiz improvements are categorized based on demographic variables and the improvement levels of different demographic groups are compared. This second assessment technique involves correlation studies between quiz performance and student demographic type which provides understanding of whether the enhancement from the ALMs is balanced across these different demographic groups. These two assessment procedures lead to two *project assessment objectives*:

1. *Determine the overall effectiveness of the ALMs.* This is primarily based on the delta between the pre-quiz and the post-quiz.
2. *Determine the effectiveness of the ALMs across different demographic groups.* This is primarily based on the quiz deltas of the different demographic groups.

This paper presents the overall results of the implementation and assessment of twelve FE modules. To provide context for this work, active learning approaches are discussed in detail in the following section. The literature review reports an overview of the research to date in active learning and provides some details on state-of-the-art active learning aspects that are particularly applicable to our work. Our FE analysis learning modules are seen in this context to be a viable active learning tool. After the active learning literature review, the focus of this work will shift to our assessment approach. The innovative assessment/demographic type correlation method is discussed below and in even greater detail in the precursor to this work (Kaufman, Wood et al. 2009). Our assessment focus, in this current work, will



delve into the specific demographic correlation results as well as the global results of the ALMs as a whole. After the results portion, possible improvements to the learning modules are discussed, focusing on how the ALMs may be iteratively refined and implemented as improved active learning tools.

ACTIVE LEARNING APPROACHES

By considering several different pedagogies in the development and assessment of the ALMs, this research endeavors to accomplish more than with any single contribution. Drawing from Bloom's Taxonomy, Kolb's Learning Cycle, Felder-Soloman Index of Learning Styles (ILS) (Felder and Silverman 1988), and Myers Brigg Type Indicator (MBTI), the ALMs are designed and assessed based on strong learning process foundations. Bloom's Taxonomy and Kolb's Learning Cycle are used in an open-loop manner to aid in the design of the ALMs. Specifically, the ALM designers create their ALMs in the context of these two questions:

1. Will a student using this ALM proceed through all four of the Kolb Cycle Quadrants?
2. Does the ALM address the appropriate level(s) in the Bloom's Taxonomy?

Once the ALMs have been created, their effectiveness in enhancing learning is assessed in a closed-loop fashion using the ILS and MBTI. Specifically, the students' pre- and post-ALM quiz scores are grouped according to their ILS and MBTI data. If one student group is determined, from their pre- and post-ALM quiz scores, to benefit more from the ALM than a different group, the ALM can be modified accordingly. For example, if the MBTI-introverts are found to benefit more from the ALM than the MBTI-extroverts, then additional collaborative learning (which tends to energize the extroverts) could be added to the ALM. The four pedagogical background theories (Kolb, Bloom's, ILS, MBTI) used to develop this work are not unique to this research, but combining their foundations to design and assess these ALMs is an original effort. Because Bloom's Taxonomy (Bloom 1956) and Kolb's Learning Cycle (Kolb 1984; Stice 1987; Brown 2004; Brown 2004) are likely familiar to the reader, they are not described in detail here. However, as we will explicitly use the MBTI and Felder-Solomon Learning Styles as foundations for our closed-loop assessment, an overview of these two theories is provided below.

Learning Styles

Each ALM was designed to span the spectrum of different styles in which students learn. The ILS is composed of four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global, as shown in Table 1. These dimensions represent students' preferences or aptitudes for learning in different manners or contexts. For example, some students prefer to learn visually, instead of



Felder-Soloman	
ACTIVE	REFLECTIVE
Doing something active with it. Discussing, applying, or explaining it to others.	Thinking about it quietly first.
SENSING	INTUITIVE
Learning facts.	Discovering possibilities and relationships.
VISUAL	VERBAL
See-- pictures, diagrams, flow charts, time lines, films, and demonstrations.	Words-- written and spoken explanations.
SEQUENTIAL	GLOBAL
Gain understanding in linear steps.	Learn in large jumps, suddenly "getting it."

Table 1: ILS Learning Style Categories.

verbally, while others have the aptitude for intuitive learning. An active learner may prefer to be very hands-on in their learning. They may have realized they learn better this way or they may just have a subconscious tendency to be very active. What is important to note though, is active learning tools are not just geared towards active learners. This is a coincidental misnomer. One of the objectives of active learning tool design is to have equal effectiveness regardless of learning styles. In order to accomplish this, ILS is explicitly used in a closed-loop feedback control fashion to iteratively refine the ALMs. Particular approaches to teaching often favor a certain learning preference. Therefore it is important to incorporate a variety of teaching approaches. Every student has a quadruple set of learning styles using the four pairs of indices. An example of a student's learning style is: Active, Intuitive, Visual, and Global. Just as there are many facets and combinations to a single student's learning preferences and capabilities, there can be many facets and combinations to a professor's teaching methods. This index, along with the active learning pedagogy provided by Kolb's Cycle and Bloom's Taxonomy, can assist instructors in creating learning modules that impact all student learning styles effectively.

The MBTI is similar to the ILS, but is linked to personality preferences, as shown in Table 2. The MBTI includes four categories of how an individual processes and evaluates information (Myers and McCaulley 1985). The first category describes how a person interacts with his or her environment.

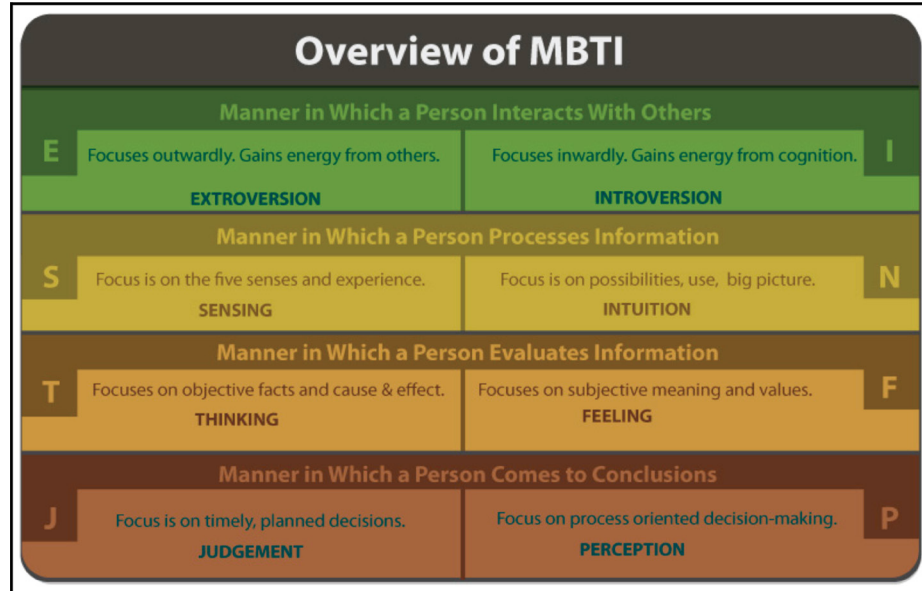


Table 2: Myers Briggs Type Indicator (MBTI) Personality Type.

People who take initiative and gain energy from interactions are known as Extroverts (E). Introverts (I), on the other hand, prefer more of a relatively passive role and gain energy internally. The second category describes how a person processes information. People who process data with their senses are referred to as Sensors (S), and a person who sees where data is going in the future is called an iNtuitor (N). The Sensor versus iNtuitor category is an interesting area of study when it comes to engineering education, because professors are historically intuitors while most engineering students are sensors (Felder and Silverman 1988). The third category for MBTI preference describes the manner in which a person evaluates information. Those who tend to use a logical cause and effect strategy, Thinkers (T), differ from those who use a hierarchy based on values or the manner in which an idea is communicated, Feelers (F). The final category indicates how a person makes decisions or comes to conclusions. Perceivers (P) prefer to be sure all the data is thoroughly considered, and Judgers (J) summarize the situation as it presently stands and make decisions more quickly. Similar to the learning style index, each individual has a set of four letters that represent their unique MBTI type. For example, an individual reporting ENFJ is an extroverted, intuitive, feeler, judger.

A number of researchers have used knowledge of MBTI types to enhance engineering education (Kolb 1984; Stice 1987; Borchert, Jensen et al. 1999; Bowe, Jensen et al. 2000). In this prior educational research, it has been shown that different MBTI types respond in unique ways to distinctive



pedagogical approaches. The goal of using the MBTI data and the learning styles data in coordination with the ALMs is to ensure the FE based ALMs are effective across different student types. This will be accomplished by using MBTI and learning styles in a closed-loop feedback control manner to iteratively refine the ALMs. This process is described in detail below.

Literature Review

Research in engineering education over the past few decades shows a general call for reform. Though considerable strides have been made in terms of adapting traditional teaching methods to meet the needs of new student generations, understandable voids still exist. Throughout this section, we discuss where the research has been focused in improving engineering education. This review involves studying and analyzing active learning tools and techniques, along with the assessment methods for determining their efficacy.

When Felder investigated learning and teaching styles in engineering education during the late 1980s, there was quite a response from the community (Felder and Silverman 1988). Felder sought to explain common pitfalls in engineering classrooms and propose a plan to improve engineering education as a whole. Drawing on the research of Kolb, Myers, and Piaget (Felder and Brent 2005), Felder looked to implement educational psychology research for his own practical purposes and for direct use in the classroom. He recognized divergences between the way most engineering students tend to learn and the way most instructors tend to teach. As early as the 1990s, engineering educators found themselves deep in the throws of this new transition of understanding the old, traditional approach for teaching engineering curriculum versus new, innovative possibilities. The traditional passive role of students is to be listeners during lectures. Any “doing” comes after class in the form of labs or homework. Felder later discusses these Changing Times and Paradigms (Felder 2004), considering active learning as the new frontier, pushing for “stimulating interactive lessons.” Smith and Waller build upon the educational reforms and lay out New Paradigms for Engineering Education (Smith and Waller 1997), which include conducting assessments in various forms to summarize the impact of active learning methods.

When it comes to active learning, the art of teaching with student engagement in mind is at the heart of the matter. Smith pinpoints the creativity involved in thinking about “How do you learn best?” and challenges educators to have more fun with both curriculum and instruction (Smith, Sheppard et al. 2005). With a focus on a particular active learning strategy, called cooperative learning, a consideration of how FE based ALMs fit into the interactions present in the classroom is warranted. Prince reviews the active learning research and provides evidence indicating that active learning improves understanding (Prince 2004). No matter the magnitude of improvement levels, it is important to note that the overwhelming response to active learning studies is positive. In an



international effort, Bernhard reports on the need for long-term results to be reviewed (Bernhard 2000). When computer science students were studied (Brenda Timmerman and Barnes 2003), increased comprehension and skills due to implementation of active learning techniques were reported. These students were thought to be the furthest from needing any form of active pedagogy, as they are often generalized as individualistic, introverted and non-social learners. Vallino goes on to discuss the need for active learning techniques, especially problem-based learning, in software development curriculum (Vallino 2003). Through this approach, students reported better test scores and appreciation for the course.

There are several efforts (Carlson and Sullivan 1999; Freuler, Fentiman et al. 2001) implementing “hands-on” engineering initiatives that lead to the discovery of “excitement of learning by doing!” The state-of-the-art in active learning involves personalized learning (Karagiannidis and Sampson 2004) where lessons are automatically adapted to fit students individual learning needs and style. “SMART” learning has been employed to develop intelligent distributed environments for active learning (Shang, Shi et al. 2001). The common thread throughout all these efforts is the focus on student-centered learning to improve education efforts.

Instructors across the country have made efforts to describe what improving engineering education means to them (Bjorklund and Colbeck 1999; Campbell 1999; Buxeda, Jimenez et al. 2001; Wood, Jensen et al. 2001; Froyd and Ohland 2005; Borrego 2007). To some, the focus is on problem-based learning, a particular type of active learning (Raucent 2001; Dym, Agogino et al. 2006). Even internationally (Berggren, Brodeur et al. 2003; Mills and Treagust 2003), initiatives have been made to redirect the focus of engineering instruction from the professor into the hands of the students. Felder’s fourfold study on The Future of Engineering Education (Felder, Woods et al. 2000; Rugarcia, Felder et al. 2000; Stice, Felder et al. 2000; Woods, Felder et al. 2000) includes efforts to push for well-rounded engineers, for instruction that improves student learning and for the criticality of applied engineering skills. Overall, the call for education reform in engineering focuses on active learning, integration of new technologies and teaching techniques, as well as faculty involvement in all efforts.

Wood and Jensen have collaborated on several “hands-on” efforts as well as the development and deployment of Active Learning Products (ALPs) to take the field of active learning in exciting new directions. Hands-on activities provide students of all learning styles and personality preferences the opportunity to get actively involved with their learning and provides for valuable experience useful in future industry work (Jensen, Wood et al. 2000; Jensen, Wood et al. 2003; Wood, Jensen et al. 2005). The idea of incorporating MBTI data has been previously examined by (Jensen, Wood et al. 1998; Linsey, Talley et al. 2007). Our latest work includes the development of assessment techniques to explore the equitability of effectiveness of the active learning techniques across



different student demographics (Kaufman, Wood et al. 2009). From this work, we created an innovative assessment algorithm that can be adapted to assess a wide variety of ALPs. Additionally, this work highlights preliminary results of ALMs, in the form of tutorials, enhancing student learning of difficult course content.

In a study conducted at the Colorado School of Mines (Olds, Moskal et al. 2005), the gamut of both assessment methodologies and experimental designs can be learned. From these comprehensive reports on current assessment methods, it can be concluded that the method presented here is a hybrid meta-analysis of chosen focus groups, using a baseline data experiment for statistical analysis and equitability correlations. According to the results reported in similar studies, selection of an appropriate assessment methodology is not a trivial process. In Felder's Longitudinal Study of Engineering, the classical method of self-assessment is chosen, with intensive time and effort devoted to produce consequent comprehensive results (Felder, Forrest et al. 1993; Felder, Mohr et al. 1994; Felder 1995; Felder, Felder et al. 1995; Felder, Felder et al. 1998). We have found from our study that it is oftentimes possible to add a supplementary self-assessment on behalf of the students (and even faculty). Educational efforts, in general, search for assessment methods that will "determine whether programs help the students they are designed to serve" (Myers and Dynarski 2003).

The spectrum of active learning provides a variety of choices for instructors to consider including: group projects, application of industry examples, integrated content tutorials, students movement, inspiration and challenge, collaboration, problem-based learning, Q/A sessions, technology and interactive student feedback. Examples of research involving these methods include Video Interaction Analysis (VIA) to study group performances during an experimental bike mechanical dissection exercise (Regan and Sheppard 1996). Problem-based learning emphasizes working in groups (Dahm, Newell et al. 2003). Further results of Felder's collaborations (Felder and Brent 2005), in addition to an active on-line version of his learning style index, include a set of teaching techniques to help address all the learning styles present in any classroom. The active learning methods that have been researched, including technical, and the psychology of education, have proven to lead to more effective and efficient teaching (Felder and Brent 2001).

In recent years, Felder participated in several research studies (Felder, Felder et al. 2002; Zywno 2003; Felder and Spurlin 2005) to validate both learning styles and MBTI effects to understand student differences to a further degree. Validation aside, there exists camps of educational researchers that resist the idea of learning styles (Cassidy 2004; Coffield, Moseley et al. 2009; Coffield, Moseley et al. 2009). Resistance and disagreement exists for several reasons, such as the lack of psychological studies that validate the actual existence of learning styles. In addition, the cognitive science community is conflicted on the validity of these techniques. Even with varying opinions, there have been numerous efforts to use the concept of learning style to further understand how students



differ, how educators can reach all students, and how to enhance learning (Felder and Brent 2005; Kolb and Kolb 2005; Hawk and Shah 2007).

This research is breaking into a new sector of combining active learning with assessment measurements for equitability correlations using the ILS and MBTI indicators. The overarching theme is the combination and extension of several useful tools to develop innovative ALMs combined with a hybrid assessment method. Disagreement with the learning styles is accepted but arguably inconsequential for this work, and does not discredit the novelty of these ALMs and the assessment method in general. Currently, there are three 'Assessment of Student Achievement' projects being funded by the National Science Foundation (NSF) Course, Curriculum and Laboratory Improvement (CCLI) programs; all varied in topics. One aims at developing a "Computerized Adaptive Dynamic Assessment of Problem-solving," another endeavors to validate engagement measurements. Our current study remains unique from what is being researched and executed in the classroom to date.

It is clear that the global engineering community is discovering the potential of experiential learning environments and the corresponding need for effective assessment methods to determine intended quality and improvement of the learning process (Berggren, Brodeur et al. 2003). In order to expect institutions to accept the paradigm shift in engineering, educators supporting this reform must thoroughly assess their efforts in implementing active learning. The task, of course, is to determine if these ALMs have a positive effect on student learning. As will be demonstrated in the following section, the procedure of designing and developing the ALM itself is very crucial. These steps insure the module contains pedagogical foundations in active learning. Another non-trivial step in this process involves choosing assessment methodologies properly.

What has been learned from this overarching research review is threefold. First, our assessment method is a hybrid of sorts, combining quantitative statistical analysis with equitability correlations. Furthermore, as shown below, evaluation from cumulative, global results demonstrates how effective the modules are as ALMs. This type of assessment method has not yet been addressed in the field and the potential is promising. Second, these learning style inventories and personality types are viewed as tools to address personality and learning preferences for all students, not a restrictive categorization limiting perspective. Whether or not ILS and MBTI are accepted as valid measures, the key point is that the assessment method can be used with the equitability measure of an instructor's choosing. Third, as detailed below, a basic content quiz was chosen to obtain the baseline data for both its simplicity and its effectiveness in assessing student learning. Other content evaluation approaches may be adapted directly with this assessment method.



DESIGN OF FE-BASED ALMS

The steps to creating the 12 FE-based ALMs can be explained using an exemplary learning module, the “Curved Beam” tutorial. Note that this is a difficult engineering topic within solid mechanics and mechanics of materials. The first task to tackle is selection of an appropriate commercial software package. The FE software available for consideration includes SolidWorks, ANSOFT, MSC.Nastran, ANSYS, Algor, and the like. Considerations include the most straightforward selection with a gradual learning curve and internal supporting software help functions. Instead of choosing software students are most familiar with, instructors should consider student ease of use as the top priority. A supplementary educational goal of these modules is to become familiar with the selected computer FE software. In terms of time, students should be able to implement the ALM using the software code and construct problem models associated with the particular FE subject matter in under an hour. The step-by-step instructions to construct the model should be easy to read and use. If possible, the software should be forgiving, or flexible. Adaptable software units can identify simple modeling mistakes and guide students through problem correction. This way, novice modelers are not penalized throughout the learning process. Together, these “help” programs can outline potential roadblocks, automate student assistance, and include internal guidance.

For “Curved Beam” ALM, the SolidWorks software was chosen. Besides meeting most of the considerations mentioned above, this software was attractive because participating students had introductory SolidWorks experience in freshman graphics courses. For the curved beam problem, the foundations were drawn from the literature, such as fundamentals from the well-known text *Mechanical Engineering Design* (Shigley, 8th edition). After initial testing, the problem could be solved by students using the module in an average of 40 minutes. With most students spending 60 to 90 minutes on homework problems, this average met desired goals of the module developers.

This specific topic was chosen for development of an ALM because students have a difficult time visualizing stress distributions in curved beams and calculating the radius of the neutral axis. Therefore, problem analysis objectives for the ALM include assisting students in determining the stress distribution, using the FE method to visually verify this distribution and using the FE method to visually verify the location the the neutral axis. Educational objectives for the module include providing students with a basic understanding of the FE method, associated constraints and boundary conditions, methods of model verification and experience with commercial FE software.

Once software has been chosen and the specific topic of study has been identified, the step-by-step procedure for the ALM is developed. Many details in the ALM are guided by the pedagogical underpinning of Kolb's Cycle and Bloom's Taxonomy. Specifically, the implementation of the ALM needs to take the student through all four quadrants of the Kolb's Cycle. The FE-based ALMs have



a variety of manners in which this can be accomplished. The “Concrete Experience” quadrant can be accomplished through the use of the real-world problem statement that the module is analyzing. “Abstract Hypothesis and Conceptualization” can be implemented by asking students to predict the results of the modeling *a priori*. The “Active Experimentation” is very much inherent in the building of the FE model. Finally, “Reflective Observation” can be promoted by requiring an explanation of the results from the model or even perturbation studies on the effects of changes in certain independent variables.

The active learning experience should also be targeted to the correct level or levels of the Bloom’s Taxonomy. What the “correct level” is, will likely be determined by the level of the course and the placement in the course sequence; with higher levels being preferred for upper level courses and for later in the course sequence.

Ideally, each module will take students through a step-by-step process similar to the following:

- Verify SolidWorks is loaded on computer
 - Open existing model in SolidWorks Simulation
 - SolidWorks Simulation study folders
- Overview of SolidWorks
 - Left side of SolidWorks window
 - Use of SolidWorks interface
 - Toolbar explanation
 - Tutorials and getting help
- Creating SolidWorks model
 - Setting the drawing units to inches
 - Assigning material properties to model
 - Applying constraints and boundary conditions to model
 - Creating split-line force to model
- Meshing the model and running the study

Building on this example, each ALM was developed with a common template presented as follows:

- Module title, author, contact information, expected completion time and references
- Table of contents
- Project educational objectives based upon ABET Criteria 3 for Engineering
- Problem description and analysis objectives
- General steps and specific step-by-step analysis
- Viewing the results of the FE analysis and comparison to another technique



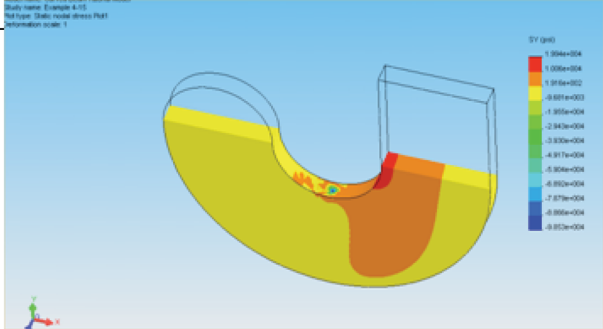
- Summary and discussion
- Background information on FE theory

Figure 1 shows the template “Module Title Page” implementation for the “Curved Beam” module.

ASSESSMENT APPROACH

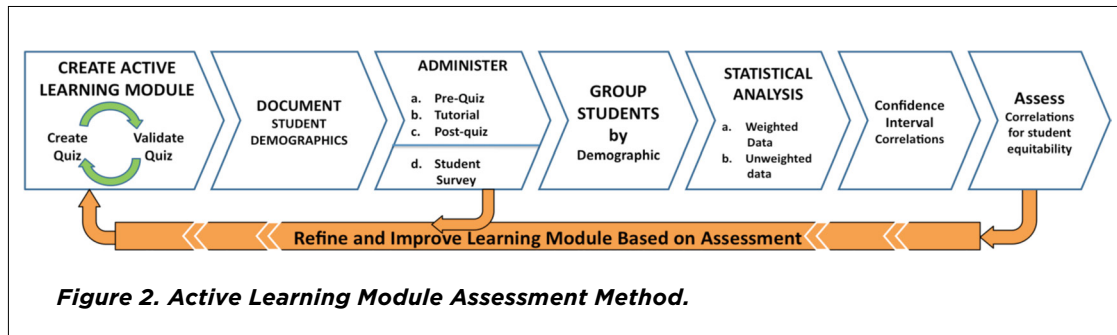
In order to achieve the project assessment goals, an assessment methodology is fully developed as outlined in Figure 2. To start, the ALM, the FE module in this case, is created. Before distributing the module, however, an evaluation content quiz (Coffman, Rencis et al., 2010) (example in Fig. 3) is created and demographic data are gathered from the students. Once the pre-quiz is administered, the module may be implemented. The post-quiz, identical in content to the pre-quiz, is taken after completion of the module. The students complete an in-depth survey (example in Fig. 4) when

Curved Beam Finite Element Tutorial



- Curved Beam Finite Element Tutorial ported to COSMOSWorks Professional 2008 Software by SolidWorks Corporation
- by Dr. Ashland O. Brown, University of the Pacific, Mechanical Engineering Dept., abrown@pacific.edu
- Expected completion time for this Tutorial 40minutes to 1 hour
- Companion Tutorial for First Machine Design Course
- Reference Text: Shigley's Mechanical Engineering Design 8th Edition by Richard G. Budynas and J. Keith Nisbett

Figure 1. Curved Beam Module Title Page.



finished. The survey allows the student to be an active member in this iterative improvement cycle. Once all the demographic data and quiz scores have been linked with common student identification, the assessment process may move to the statistical analysis phase.

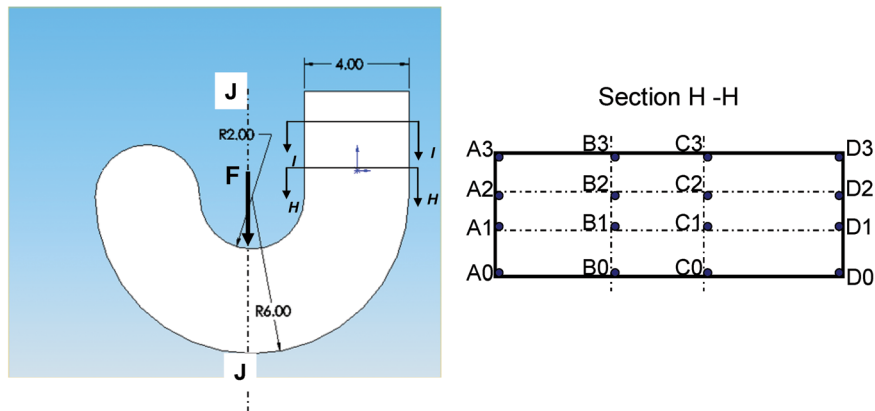
Figure 2 summarizes this assessment approach. This assessment algorithm provides two opportunities for iterative feedback with the student: surveys and confidence intervals. Students have a direct opportunity to express their opinions about how well the modules enhanced their learning experience through the survey shown in Figure 4. In addition, the demographics equitability correlations are carried out using confidence intervals and are explained in detail in the precursor to this work (Kaufman, Wood et al. 2009).

The next significant step in the assessment process is the calculation of statistical correlations. Once an evaluator decides upon a demographic group to study, the student quiz score results are grouped according to the chosen demographic. Common empirical numbers may be analyzed, e.g., mean, mode, median. Specifically, the analysis is used to determine if the performance differences, *deltas* [(post-quiz score) minus (pre-quiz score)], are statistically distinct between pairs of learning styles and personality types. In order to determine this distinction, the data are treated as a sample of a theoretical larger population. *Student-t* distributions are used for the statistical analysis, as the sample sizes are relatively small for this study. Using confidence intervals, the evaluator determines if there is any significant statistical difference between how the FE module is reaching individual students across demographic groups. For example, if an extroverted group has an average delta smaller than the introverts, confidence intervals measure the likelihood of a practical difference existing.

The online learning style and personality surveys return results indicating learning preference for the individual in each of the four categories and also includes a weight or strength for that preference. These data allow one to differentiate, for example, between someone who is only slightly “active” over “reflective” in their learning style and someone who very strongly prefers an “active” to “reflective” learning environment. The average quiz scores and change in scores (*deltas*) are



Student ID: _____



Circle the best answer

- The normal stresses at points at A0, A1, A2, and A3 are the same.
a) True b) False
- The normal stresses at points at A0 and D0 have the relation as follows.
a) $\sigma_{A0} > \sigma_{D0}$ b) $\sigma_{A0} < \sigma_{D0}$ c) $\sigma_{A0} = \sigma_{D0}$
- The stress at the center of the cross section area is zero.
a) True b) False
- The maximum normal stress occurs at the following sections:
a) A0-A3 section b) D0-D3 section c) Both A0-A3 and D0 –D3 sections.
- The shear stress at any points located on the cross-section A0-A3-D0-D3 is zero.
a) True b) False
- The maximum stresses on section A0-A3 is equal to its normal stress.
a) True b) False c) The question doesn't make any sense
- The maximum shear stress occurs on section A0-A3.
a) True c) False c) Both answers are wrong
- The stress distributions on Section H – H and Section I – I are the same.
a) True b) False
- The stress level of the hook's left portion from section J – J is zero.
a) True b) False

Figure 3. Beam Bending Basic Knowledge Quiz (Pre and Post for Curved Beam Tutorial).



Student ID: _____

Please put an X in the box below that corresponds to your answer.

Question	Disagree	Partly Disagree	Neither Agree nor Disagree	Partly Agree	Agree
This activity helped me understand “curved-beam bending” in a conceptual manner.					
This activity helped me to understand the stress distribution in the curved beam.					
This activity helped me to visualize the stress distribution in the curved beam.					
This activity helped me to have a better understanding about the deformation of the curved beam under the concentrated load.					
This activity will help me to design a better curved beam to undertake a larger load.					
This activity helped to locate the points where the normal stress is zero.					
Activities like this one doesn’t require full understanding of the FE theory.					
This activity helped me to create a correct FE model from 3D CAD model for stress analysis.					
This activity helped me to learn how to apply the force, add constraints and create meshes for FE models.					
After completing this activity, I was able to implement a simple FE analysis using COSMOS.					
This activity was more effective than class time for lecture or board-work in terms of understanding the stress distribution.					
The FE analysis method is more useful and efficient to get all stress information for a structural member.					
I would like to learn more on using the FE method to solve other mechanical engineering design problems.					
Totals					
Percentage of Students Selecting Response					

Figure 4. Sample Students Survey.

weighted using linear interpolation according to the weights reported from the corresponding learning style or personality survey for each student. The confidence intervals are calculated across the unweighted and weighted deltas.



The data collected for this work is a part of the NSF funded CCLI project analogous with the FE ALM development. Several universities across institution type and student diversity assisted in implementing each module in corresponding engineering classrooms. Professors were given previously developed modules along with other tools and then asked to return as much data as possible. The tools and data used in this work are discussed below.

The breadth of resources used throughout this assessment process covers a significant breadth of research standards. Professors traverse the process of using the tools provided to produce learning and assessment data. Resources classified as tools include each of the FE modules, the corresponding content quiz used for pre- and post-evaluation, student surveys, and the learning style and personality type index resources. The ILS and the MBTI were chosen as assessment qualifiers. Though MBTI varies slightly from strict personality types, we will differentiate between the two demographics simply as learning styles and personality types. Informal tools that arose during the study include professor feedback and quiz validation. Data sets studied include results of pre- and post-quizzes, indices inventories and survey responses. Specifically, the assessment work focuses on the results that correlate the quiz scores to learning styles and personality type. More generally, the global improvements in quiz scores can help determine the effectiveness of the modules as active learning tools.

RESULTS

Below the authors show results for two specific demographic correlations using a representative ALM; in this case the Heat Transfer FE module. As shown in Table 3, the students in this particular class used the ILS questionnaire to determine their learning styles (<http://www.engr.ncsu.edu/learningstyles/ilsweb.html>). The pre- and post-quiz results were categorized based on the learning styles of the students. Small sample statistics (*student-t*) were used to provide the statistical analysis. The students took the pre-quiz, then completed the ALM and then took the post-quiz. The percentage improvements between the pre- and post-quiz are recorded in Table 3 for each of the learning style categories. Recall that the learning style categories are paired. So a student is either “Active” or “Reflective”, either “Sensing” or “Intuitive”, either “Visual” or “Verbal” and either “Global” or “Sequential.” The average Delta (percent improvement) for each category is calculated and compared for each learning style using the following equation:

$$\text{Delta} = \left(\frac{\text{postquiz} - \text{prequiz}}{\text{prequiz}} \right) \times 100$$



Heat Transfer									
Learning Style	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Global	Sequential	Average
Number of Students	9	3	5	7	10	2	5	7	6
Delta (% Improvement)	6.3	14.3	5.7	10.2	8.6	7.1	11.4	6.1	8.7
Standard Deviation	17.7	14.3	16.3	17.9	18.1	10.1	21.2	13.9	
Weighted Delta	4.8	9.9	7.3	12.0	7.7	11.9	6.3	9.6	8.7

Table 3: Heat Transfer ALM Results (ILS Pairs).

The goal of this analysis is to determine if one learning style is benefiting more from the ALM than another learning style. From Table 3 it can be seen that the Delta for the “Reflective” learners is 14.3% while it is only 6.3% for the “Active” learners. The “weighted” data in the table comes from the fact that the input from the ILS questionnaire not only provides a student’s four learning propensities (either “Active” or “Reflective”, either “Sensing” or “Intuitive”, either “Visual” or “Verbal” and either “Global” or “Sequential”), but also provides the strengths of these propensities. For the weighted data, we simply use a linear extrapolation to weight the data in accordance with the strength of these propensities. As a simple example, if we have 2 students who are both “Active” learners where student “A” has a propensity strength of 9 while student “B” has a strength of 5, then student “B’s” Delta score will contribute less toward the Delta for the “Active” learners. If student “A” has quiz scores with a Delta of 10% and student “B” has a Delta of 20%, then the unweighted average is $(10+20)/2 = 15\%$. The weighted average is computed using the following equation:

$$\text{Weighted Delta} = \left(\frac{9 \times 10 + 5 \times 20}{9 + 5} \right) = 13.6$$

The extra strength of the active learning propensity of student “A” can be seen to pull the average toward their value and away from that of student “B.” This approach represents a more accurate measure of how generic active learners would respond to the ALM. Table 4 shows confidence intervals for the pairs of data in Table 3. The confidence intervals answer the question: are the averages in Table 3 really statistically different? The number of data points, averages and standard deviation are used in standard small sample size (*student-t*) manner to compute these confidence intervals. Note in Table 4 that the largest value is associated with the differences in the averages for unweighted “Reflective vs. Active” data. Specifically, there is a 52.3% chance that the 6.3 and



Heat Transfer		
Learning Style Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
Reflective vs. Active	52.3	35.6
Intuitive vs. Sensing	33.8	34.7
Verbal vs. Visual	10.9	31.1
Sequential vs. Global	35.8	22.8

Table 4: Heat Transfer ALM ILS Correlations.

Heat Transfer									
Learning Style	Extrovert	Introvert	iNtuit	Sensor	Thinker	Feeler	Judger	Perceiver	Average
Number of Students	5	7	8	4	6	6	10	2	6
Delta (% Improvement)	8.6	8.2	10.7	3.6	4.8	11.9	3.1	36.8	8.4
Standard Deviation	21.7	13.9	16.6	18.0	17.3	16.7	18.1	0.0	
Weighted Delta	2.6	6.4	10.3	10.5	3.9	17.2	2.4	14.3	8.4

Table 5: Heat Transfer ALM Results (MBTI Pairs).

14.3 average values for “Active” and “Reflective” learners in Table 3 are actually different. Restated in the nomenclature of this present research, there is a 52.3% chance that the “Reflective” learners benefit more from the ALM than do the “Active” learners.

The MBTI based data shown in Tables 5 and 6 follows the same analysis pattern as that for the ILS data in the previous two tables. Note in Table 5 that there are large differences in the standard (unweighted) Deltas for the “iNtuitors vs. Sensors”, Thinkers vs. Feelers” and for the “Judgers vs. Perceivers.” The weighted Delta data shows large differences between the “Thinkers vs. Feelers” and also for the “Judgers vs. Perceivers” but not for the iNtuitors vs. Sensors. These large Deltas lead to large confidence intervals as shown in Table 6.

Specifically note the values in Table 6 which are over 50%. These values indicate that there is greater than a 50% chance that one MBTI type is receiving greater benefit from the ALM than the



Heat Transfer		
Learning Style Differences	Unweighted Confidence Interval (%)	Weighted Confidence Interval (%)
Reflective vs. Active	2.8	25.8
Intuitive vs. Sensing	46.4	1.7
Verbal vs. Visual	51.4	79.2
Sequential vs. Global	60.6	93.1

Table 6: Heat Transfer ALM MBTI Correlations.

opposite MBTI type. These circumstances indicate opportunities for iterative, directed refinement of the ALMs. In this particular case, since the MBTI-Thinker and the MBTI-Judger groups did not benefit as much as their counterparts (MBTI-Feeler and the MBTI-Perceiver groups, respectively), the iterative refinement plan calls for specific steps that should enhance the active learning experience for these two groups. For example, to improve the experience for the MBTI-Thinkers, reformatting the homework questions included in the module in a way that leads the student through a step-by-step, logical process to increase their understanding of the physical principles being modeled should fit well with the “thinkers” preferences. In addition, making sure that the instructions in the FE modules include explanations indicating what specifically a step in the simulation process is accomplishing should also enhance the experience for the MBTI-Thinkers. To enhance the ALM for the MBTI-Judgers, one critical item is to have an accurate estimate of the time needed to complete the ALM. Also, a detailed outline of the ALM content and process will allow the MBTI-Judgers to schedule their work and keep track of their progress.

While Tables 3-6 show an example of the ILS and MBTI correlation studies for a single ALM, Table 7 shows the overall results cumulatively for all 12 ALMs. This data can be addressed very methodically. First, there are a total of 12 ALMs to assess, each with unique subject matter spanning many engineering disciplines. Then, the number of students who participated in the module study can be determined. Almost 150 students participated in the first round of each FE learning module implementation into the classroom setting. An average of 12 students were in each class using the ALM to supplement the curriculum. For each ALM, the average pre-quiz score for the groups of students can be seen, ranging from 42% to 71% correct. The overall average of all pre-quiz scores pertaining to all 12 FE modules was 58.6%, well below passing. The overall post-quiz average of 75.5% shows



FE Learning Module Subject	Students	Pre-Quiz Avg	Post-Quiz Avg	Delta	Percentage
Curved Beam Structural Analysis	9	71.1	82.2	11.1	15.6%
Stiffness Bolt Structural Analysis	12	55.8	65.0	9.2	16.4%
Long Bar Heat Transfer	19	63.1	72.9	9.8	15.5%
L-Bracket Transient Heat Transfer	19	63.1	72.9	9.8	15.5%
Biomedical Electromagnetics	6	50.0	76.7	26.7	53.3%
Fluid Dynamics Cylinder Drag	7	62.9	77.1	14.3	22.7%
Fluid Dynamics Friction Flow	7	62.9	77.1	14.3	22.7%
Vibration of Cantilever Beam	7	49.9	79.6	29.7	59.6%
Vibration of Tapered Beam	16	58.0	72.3	14.3	24.6%
Microstrip Antenna Design	10	60.0	81.3	21.3	35.5%
Sar Analysis	20	63.8	81.5	17.7	27.7%
2D Transmission Lines	10	42.5	67.5	25.0	58.8%
Total :	142				
AVERAGES :	11.83	58.6	75.5	16.9	30.7%

Table 7: Cumulative Results of FE Modules based on Student Performance.

significant improvement, with an individual range on the 12 modules of 65% to 82% correct. Results indicate that on average, students are not passing the content pre-quiz, but after being administered the module, the average student improves their post-quiz score to well above passing. On a strictly percentage base improvement scale, it becomes clear that there is an average Delta of almost 17 raw percentage points. This can be directly translated as grade enhancement of slightly more than a letter grade and a half using a traditional grading scale. Looking at the improvement on a relative percentage basis, there is an average improvement of 30%. For example, on the Microstrip Antenna Design module, scores improve from an average of 60% to over 80%, equating to an improvement of 35.5%. The range of percentage improvements starts at about 15% and goes up to nearly a 60% improvement.

These cumulative results allow us to consider a global perspective on the effectiveness of the modules. As active learning tools, we asked if these particular ALMs were enhancing student learning. From these initial results the following conclusions can be drawn:

1. On average, the ALMs assist students learning the material with an average 30% improvement in content knowledge,
2. Student quiz scores improve from below passing to above passing by almost two letter grades on average, and
3. The modules have been piloted in 12 different classrooms. Based upon the successful results of a single iteration of ALPs development, the potential opportunity for improved learning appears to be significant.



CONCLUSION AND FUTURE WORK

Active learning provides future engineers with the opportunity to be more involved in their own education. To date, 12 Finite Element (FE) based Active Learning Modules (ALMs) have been designed and developed using proven active learning pedagogical foundations. The specific topics for the ALMs were chosen from topics that historically have been difficult for students to comprehend and which could be modeled using FE analysis. The two project goals were to use active learning to enhance student understanding of these difficult engineering concepts using FE-based ALMs and to increase exposure and understanding of the FE method for undergraduate engineers. In order to accomplish these goals, an extensive assessment strategy was developed and implemented. The strategy, and associated assessment instruments and processes, are designed to accomplish two assessment goals: 1) to determine if the ALMs enhance the learning process for the students and 2) to determine if the ALMs benefit one student demographic group more than another group. The assessment/student demographic correlations allow us to iteratively enhance the ALMs to make them more effective across all student demographic groups.

The cumulative results of all 12 FE-based ALMs were very positive. From the correlations, areas of improvement for future iterations of particular ALMs are identified. From the presented correlations it can be concluded that confidence intervals (Tables 4 and 6) less than 50% suggest the ALP has been designed with an appropriate balance of pedagogical content to provide an equal learning benefit to each pair of opposing learning styles (e.g. MBTI Extrovert vs. Introvert) as well as learning propensities (e.g. MBTI Extrovert/Introvert, iNtuit/Sensor, Thinker/Feeler and Judger/Perceiver). On the other hand, confidence intervals greater than 50% suggest the ALP contains pedagogical content that is more conducive to a particular learning style and could, therefore, benefit from a directed refinement of the ALP content to improve the learning potential of the specific learning style students who under-performed on the post-quiz assessment. On a whole, the average improvement to student learning directly related to these ALMs is significant. The ALMs provide students with the chance to go from below passing on content quizzes to significantly above passing. Specifically, the assessment over the 12 ALMs indicates an average pre- to post-quiz score increase of over 30%. The iterative assessment method presented has identified numerous demographic groups that benefited less than other groups from the initial implementation of the ALMs. This provides the potential to refine and improve each ALM in order to proceed toward the goal of a balanced benefit from the ALMs across numerous student demographic groups.



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Daniel J. Jensen is a Professor of Engineering Mechanics at the U.S. Air Force Academy. He received his B.S., M.S. and Ph.D. from the University of Colorado at Boulder. He has worked for Texas Instruments, Lockheed Martin, NASA, University of the Pacific, Lawrence Berkeley National Lab and MacNeal-Schwendler Corp. His research includes development of innovative design methodologies and enhancement of engineering education.



Joseph J. Rencis is Professor of Mechanical Engineering at the University of Arkansas. From 2004 to 2010, he was Department Head and the inaugural holder of the Twenty-first Century Leadership Chair in Mechanical Engineering from 2007 to 2010. Dr. Rencis is an inaugural fellow of the Southeastern Conference Academic Consortium Leadership Development Program. From 1985 to 2004 he was at the Worcester Polytechnic Institute, serving as Director of Engineering Mechanics from 1995 to 2004. He received a B.S. from Milwaukee School of Engineering, M.S. from Northwestern University, and Ph.D. from Case Western Reserve University. He is a fellow of the American Society of Mechanical Engineers (ASME), American Society of Engineering Education (ASEE),



and Wessex Institute of Great Britain. He is a ABET program evaluator and member of the National Collaborative for Engineering Graduate Education Reform.



Kristin Wood is the Cullen Trust Endowed Professor in Engineering and University Distinguished Teaching Professor at The University of Texas at Austin, Department of Mechanical Engineering. Dr. Wood's current research interests focus on product design, development, and evolution. The current and near-future objective of this research is to develop design strategies, representations, and languages that will result in more comprehensive design tools, innovative manufacturing techniques, and design teaching aids at the college, pre-college, and industrial levels.



John J. Wood is an Associate Professor of Engineering Mechanics at the United States Air Force Academy. He completed his Ph.D. in Mechanical Engineering at Colorado State University and is a retired Air Force officer. The current focus of Dr. Wood's research includes the pioneering development of micro air vehicle systems using innovative conceptual design techniques for current technology implementations, as well as futuristic projections, applied in the framework of a senior capstone design course. Other research areas include the integration of modern pedagogical theory and learning styles with interactive, computer-based multimedia instruction of advanced undergraduate structures-based engineering courses.



Christina White earned her M.Ed. in Special Education from The University of Texas at Austin and her Doctorate in Curriculum and Teaching from Columbia University. Engineering Education for Social and Environmental Justice is a passion in Christina's scholarship and profession. She facilitates engineering experiences towards actively engaging in democratic practices. This is done through her interdisciplinary and international curriculum development and teaching. Her dissertation research is entitled "Taking **HEED**: Intersections of Women's Lives in Humanitarian Engineering Experiences and Design." From her patented *Automated Assistive Guitar Playing Device* to directing the Design, Technology, Engineering for All Children (DTEACH) program



at the University of Texas at Austin. Christina's practices and research inform ways that we understand engineering education and innovation in our diverse and dynamic ecology.



Kristen Kaufman Raaberg attended the University of Texas at Austin for her B.S. in Mechanical Engineering '08 and her M.S. in Mechanical Engineering '09. Her graduate work focused on engineering education, especially active learning and how we can learn from students' learning styles. She studied under Dr. Kristin Wood and Dr. Richard Crawford.



Josh Coffman completed his M.S. in the Department of Mechanical Engineering at the University of Arkansas, Fayetteville in 2010. He is currently employed as a Civil/Structural and Piping design engineer for Entergy Operations, Inc. at Arkansas Nuclear One. He received a B.S. in Mechanical Engineering from Arkansas Tech University in 2006, while working as a civil design technician for Crafton, Tull, Sparks, and Associates in Russellville, Arkansas.